Analyzing Residential Electricity Consumption Patterns Based on Consumer's Segmentation

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Abstract. The identification of energy consumption patterns contributes for the tailoring of energy efficiency solutions. This paper contributes to this issue by addressing the characterization of electricity consumption data with 15 min sampling of twenty two households, in Lisbon. The consumers have been segmented according to: social class, contracted power, number of rooms, family size and type of tariff (flat or dual prices). Social class has been estimated according to education and income. The results show that consumption behavior has a stronger association with inner values rather than the habitation characterization. In fact, families who have chosen non-flat tariff consume less electricity than remaining ones. Such a choice should be a consequence of a higher energy (and cost) consciousness associated to the choice of a dual-tariff and a consequent decrease of electricity consumption. Social class can be a reflection of income but, more than that, a reflection of education, knowledge (also energy-related knowledge), values and amount and performance of the existing appliances. For this reason, such factors should be analyzed more intensively by crossing consumption to occupancy and equipment efficiency, as well as socio-economic characterization, resourcing to social sciences expertize. With the proper consumers' characterization, the design of energy efficiency solutions should be more effective.

Keywords. Consumers' segmentation, energy efficiency, electricity consumption patterns, design of energy efficiency solutions.

1 Introduction

The search for energy efficiency is a priority for the achievement of a more sustainable society. The goals established by the European Union (EU-27) in the 20-20-20 targets by 2020 are an example of such a concern. [1]

Several references can be found in the literature which underline the importance of achieving energy efficiency in the buildings sector in particular, and that is reflected by the several ongoing works that are being undertaken in this concern, both regarding consumption behavior [2, 3] and equipment performance [4, 5]. For example, in

Portugal, the electricity consumption in the building sector accounts for 60% of the total share (29% concerning the residential sector and 31% concerning the service sector) [6]. However, to develop energy efficiency measures, it is important to understand the consumers and their consumption patterns.

This paper addresses the characterization of electricity consumption in the residential sector using the electricity consumption data from 22 households using electricity meters with a sampling time of 15 minutes, provided by the company ISA (Intelligent Sensing Anywhere). The goal is to characterize the electricity consumption patterns based on the segmentation of the households by features considered to be correlated to the consumption.

A proper consumers' segmentation contributes for the achievement of energy efficiency solutions since it allows the recognition of the influence of different factors in energy consumption. Though several factors can influence the energy consumption in a household (e.g. family dimension or income of the family) others can overcome, such as socio-economic ones (e.g. values, culture or education) [3]. After defining the influence of different factors in energy consumption for each household, the proper approach for the design of energy efficiency solutions can be undertaken. In fact, if technical factors are defined as the main ones that influence energy consumption, engineering solutions are required but if socio-economic factors are defined as the most important ones, social sciences are required for the design of energy efficiency solutions.

In [7], pattern recognition was achieved for the definition of consumption habits, based on working/weekend days and the respective temperature, concluding that such pattern recognition can be useful to improve small scale forecast and to enable tailor-made energy efficiency solutions. In [3], the energy-behavioral characterization is addressed and it is concluded that factors such as beliefs, motives and attitudes can define consumption patterns and, with that, the proper interventions for energy efficiency can be undertaken. In [8], occupancy and electricity consumption is predicted through the detection of internet usage in a university campus. The automation is again used with behavior prediction features in [9]. In fact, consumption behavior prediction is important for the development of a more efficient energy system, on which the balance between production and demand is better achieved and one can reduce energy losses and pollution generation [10-13].

The studied segmentation parameters considered in this paper are social class, contracted power, number of existing rooms, family dimension and type of tariff, given particular focus on social class due to the known impact that income can have on energy consumption [14-17]. The correlation between these parameters and the analyzed families' electricity consumption is assessed in this work.

2 Methodology

This experiment is part of a research project on energy efficiency that is being developed in the Vergílio Ferreira School in Lisbon (Lumiar and Telheiras area). Fifty households are being monitored, belonging to the students' families. However, for now, due to some technical issues, only twenty two have provided acceptable data.

During the electricity meters installation (during the first months of 2012), a survey was applied for the family social characterization, as well as to characterize some technical aspects of the household, such as the existing appliances. The data presented in this paper concerns from May 1st to June 30th, 2012.

From different possible characteristics, we chose to analyze the social class (A – high, B – Moderate, C – Low), contracted power, number of existing rooms, family dimension and the type of tariff (flat or dual-tariffs). The characterization of these parameters is depicted in Table 1, accordingly to the respective social class.

Table 1. – Different socio-economical parameters according to the social class, for the analyzed families.[1]

	Social class A	Social class B	Social class C
Contracted power [kVA]	8.5 (1.8)	8.7 (2.8)	5.4 (2.7)
Family dimension [#]	4.5 (0.9)	3.8 (0.9)	4 (1)
Number of rooms [#]	4.3 (0.5)	3.4 (0.8)	2.6 (0.8)
Simple tariff share [%]	50	30	90
Total consumption [kWh/day]	10.7 (2.7)	10.7 (3.1)	11.3 (5.1)

From the table, it is possible to conclude that the households with families of social class C tend to have less contracted power, a smaller number of rooms and a very high share of flat rate.

Regarding the families of class A, they present the highest family dimension and number of rooms, which is coherent with the current socio-economic profile of the Portuguese society.

Concerning the total electricity consumption, there is no significant differences, albeit families from social class C present a slightly higher average value (5.6% higher). However, the respective standard deviations show that the samples are disperse, mainly in social class C, followed by B and by A.

Besides the twenty two analyzed families, there were two families that were considered to be outliers, since the total consumption is 3.3 kWh/day (from a household of social class A) and 26.2 kWh/day (from a household of social class B) which correspond to 29% and 144% of the average consumption respectively (10.7 kWh/day for both social classes, with a standard deviation of 2.7 and 3.1 kWh, respectively).

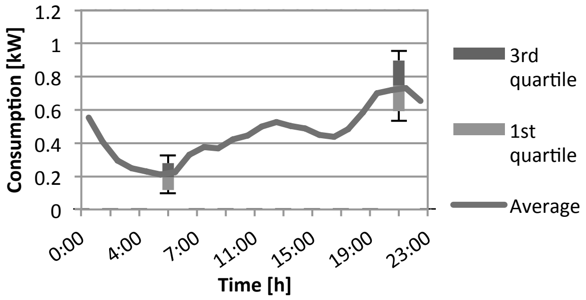
In the next section, we analyze the results in greater detail. The results' analysis is split in the average consumption in the different parameters.

[1] Values represent the average. Standard deviations are represented in brackets.

3 Detailed analysis and discussion

3.1 Daily profile

Figure 1 displays the average electricity consumption profile for the 22 analyzed families, with a boxplot for the off-peak hour (5h15) and peak hour (22h15).



	5h15	22h15
average	0.20	0.74
max	0.48	1.13
3rd quartile	0.28	0.90
median	0.19	0.75
1st quartile	0.12	0.59
min	0.03	0.35

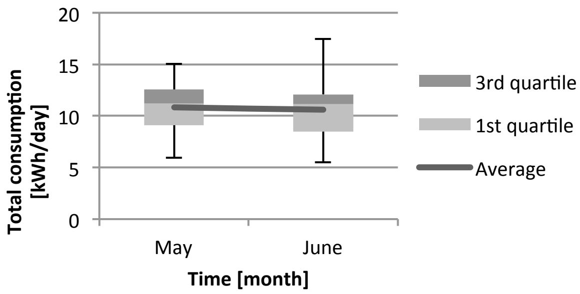
Fig. 1. – Average electricity consumption profile & statistical significance parameters, for the analyzed families.

The lowest consumption occurs at 5h15, with an average value of 0.20 kWh. The first and third quartiles of the sample are 0.08 kWh (40%) below and above the average value, respectively.

The highest consumption occurs at 22h15, with an average value of 0.74 kWh. The first and third quartiles are 0.15 (20%) and 0.16 kWh (22%), below and above the average value, respectively. In average, there are two other peak values: immedialty before 8h00 and another around 13h30.

Different consumption habits are integrated in this average profile, contributing to the identifyed variations. In fact, while some households have someone permanentely inhouse (family member or housecleaner), others have people only in the morning and evening time. Further, this profile does not distinguish weekdays from weekends.

Figure 2 displays the electricity consumption evolution in May and June 2012.



	May	June
average	10.8	10.6
max	15.1	17.4
3rd quartile	12.5	12.1
median	11.2	11.2
1st quartile	9.1	8.5
min	6.0	5.5

Fig. 2. – Average electricity consumption evolution & statistical significance parameters, between May and June.

The accumulated average consumption decreased slightly, from May to June (10.8 to 10.6 kWh, which is less than 2%). The values of the first and third quartiles, for the month of May, are 1.7 (16%) and 1.1 kWh (10%) below and above the average value, respectively. For the month of June, the values of the first and third quartiles are 2.5 (24%) and 1.5 kWh (14%) below and above the average value, respectively. Therefore, the sample dispersion has increased.

3.2 Social Class

Figures 3 to 6 analyze the consumption profile by social class in detail.

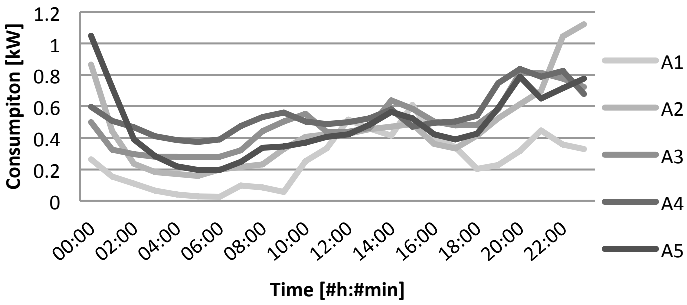


Fig. 3. – Average daily electricity consumption profile for social class A.

Regarding social class A, one can realize that the electricity consumption profiles are very similar, with the exception of the one associated to family A1, which is lower than the remaining and, therefore, contributes to lowering the average consumption.

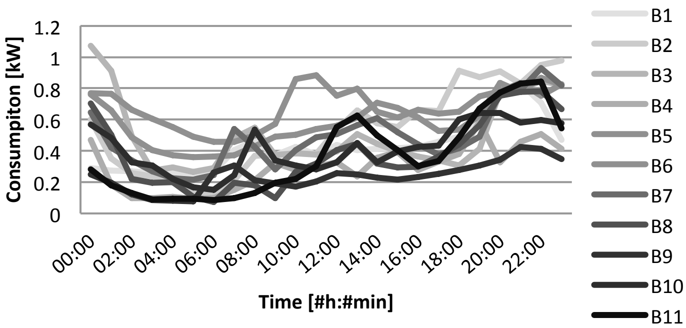


Fig. 4. – Average daily electricity consumption profile for social class B.

The consumption profile of the families of social class B is more disperse. Family B7 presents a higher consumption profile, especially during the day, which contributes to the increase of the average consumption profile.

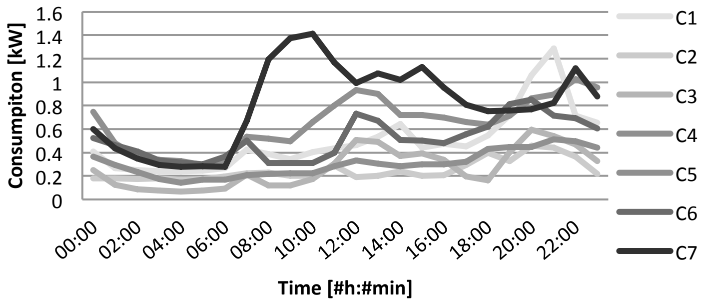


Fig. 5. – Average daily electricity consumption profile for social class C.

Social class C has the higher standard deviation value (5.1 kWh/day), reflecting a more disperse sample as can be seen in Figure 5. It can be also noticed that family C7 has a distinguished higher consumption profile from the remaining families, which increase the average consumption profile.

The total elelctricity consumption profiles, for the different social classes, is displayed in Figure 6.

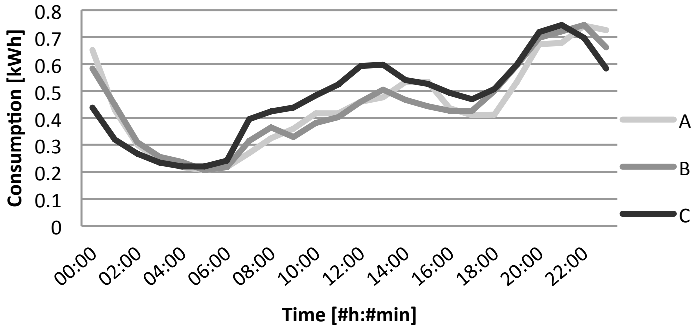


Fig. 6. – Average daily electricity consumption profile for the different social classes.

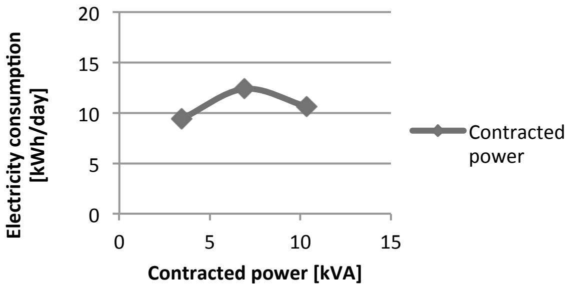
A higher consumption for social class C is displayed, while social classes A and B have close consumption profiles. Social class C has higher consumptions during the afternoon, which can reflect the presence of active people during the day (e.g. retired or unemployed people), more than in the remaining social classes.

Higher social class level can induce higher consumptions due to the fact that income is not a restriction and the number of existing appliances can be higher. However, other factors are probably more important, such as education, energy efficiency awareness and better performance of the existing equipment.

Concerning the houses occupancy; the following events were identifyed: family A1 was out of home for one day, family B6 was out of home for two days, family B10 was out of home for two days and family C1 was out of home for one day. In total, social class A has four vacation days, social class B has one vacation day and social class C has one vacation day, meaning that social class A has the presented consumption values lowered due to more vacation days than in the remainins social classes.

3.3 Contracted power

Concerning the contracted power with the utility, the electricity consumption is presented in Figure 7.



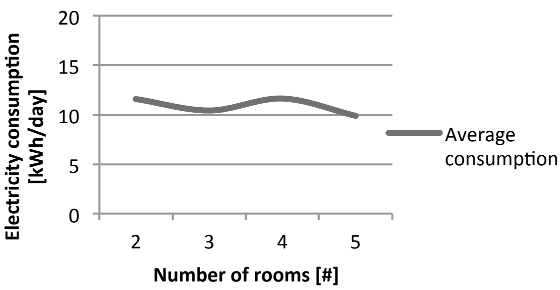
	3.45	6.9	10.35
n	6	8	8
max	13.9	16.3	19.4
min	6.0	7.0	5.7
average	9.4	12.4	10.6
standard deviation	3.3	2.9	4.4

Fig. 7. – Average daily electricity consumption & statistical sigificance parameters, by contracted power.

Electricity consumption is aperantly lower in families with contracted power of 3.45 kVA (9.4 kWh/day). However, to contracted power 10.35 kVA does not correspond to the highest consumption value - this corresponds to 12.4 kWh/dayat contracted power of 6.9 kVA. This fact shows that contracted power is not diretcly related to the total consumption, albeit it can be associated to other factors: either these households have higher peak consumptions or their contracted power is overdimensioned. It should be noted that this is in general the contracted power suggested by the utilities given the current set of appliances that exist in as typical household.

3.4 Number of rooms

Concerning the number of rooms in the houses, Figure 8 displays the electricity consumption variation with this parameter.



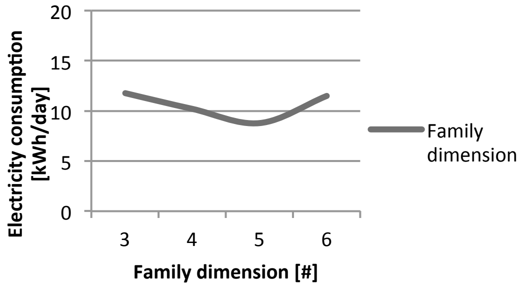
	2	3	4	5
n	5	10	5	3
max	19.4	16.3	15.6	12.7
min	5.9	7.0	5.7	6.1
average	11.6	10.4	11.6	9.9
standard deviation	5.6	2.7	3.7	3.4

Fig. 8. – Average daily electricity consumption & statistical significance parameters, by number of rooms.

A direct correlation between electricity consumption and number of rooms is not visible, as the lowest value (9.9 kWh/day) corresponds to the highest number of rooms (5 rooms) and the highest value (11.6 kWh/day) to both 2 and 4 rooms per house. The standard deviation values for number of rooms 2, 3, 4 and 5 is 5.6, 2.7 , 3.7 and 3.4 kWh respectively, which corresponds to a deviation of 48, 26, 32 and 34% from the average value.

Family dimension

Figure 9 gives the electricity consumption variation with the family dimension.



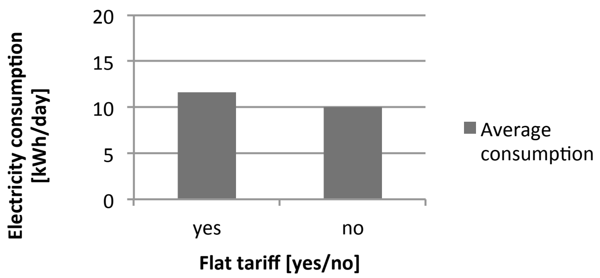
	3	4	5	6
n	7	12	1	3
max	19.4	16.3	8.8	15.6
min	5.7	5.9	8.8	6.1
average	12.2	10.2	8.8	11.5
Standard deviation	4.2	3.1	-	4.9

Fig. 9. – Average daily electricity consumption & statistical sigificance parameters, by family dimension.

The houses with 3 persons are the ones that have a higher average consumption (12.2 kWh/day), with a standard deviation value of 4.2 kWh (34% of the average value). The second highest are the houses with 6 family members, with an associated electricity consumption of 11.5 kWh and standard deviation of 4.9 kWh (43% of the average value). The houses with 4 persons have an electricity consumption of 10.2 kWh and a standard deviation of 3.1 kWh (30% of the average value). The 5 persons set is composed only by one sampleand an electricity consumption of 8.8 kWh/day. Once again, it is not visible a direct correlation between consumption and the number of persons in the household.

3.5 Type of tariff

Figure 10 displays the electricity consumption with the type of tariff. The decision to have a non-flat contracted tariff relates to a higher energy (and or cost) consciousness, since it requires to study the benefits from such a tariff and a capacity of changing consumption behaviors to obtain a higher economic benefit.



	Yes	No
n	12	11
max	19.4	16.3
min	5.9	5.7
average	11.6	10.0
Standard deviation	4.0	2.9

Fig. 10. – Average daily electricity consumption & statistical sigificance parameters, by tariff (if flat tariff is chosen or not).

The families with non-flat tariff have an average consumption 9% (10.0 kWh/day) lower than the ones with flat tariff (11.6 kWh).

4 Conclusions

This work fosters the discussion on energy efficiency concerning the identification of consumption patterns based on user´s segmentation. Proper energy consumers' segmentation is sought but its general applicability is questioned, as the presented results show.

The presented work still lacks on representativeness due to the limited sample population (twenty two households) and limited analysis period (two months). However, the electricity consumptions of the studied families will continue to be measured for a whole year, which should reveal more representative results.

The segmentation (social class, contracted power, number of existing rooms, family dimension and type of tariff) shows that the samples are dispersed and that none of the parameters displays strong correlations to electricity consumption. However, the non-flat tariff shows a correlation to smaller electricity consumption. This result can be interpreted as a reflection of a higher energy (and cost) consciousness associated to the choice of a dual-tariff and a consequent decrease of electricity consumption.

Social class can be a reflection of income but, more than that, a reflection of education, knowledge (also energy-related knowledge), values and amount and performance of the existing appliances. These factors can vary in the same social class and for this reason social class cannot be a general-applicable segmentation feature without being undertaken more intensive analyses, crossing consumption to occupancy and equipment efficiency, as well as socio-economic characterization resourcing social sciences. With more representative results and with a more intensive characterization of the households, one should be able to define consumption patterns according to defined characterization factors and, with that, the proper solutions could be designed. If those factors are considered as dependent on socio-economic factors, the help of social sciences for the definition of such solutions should be required.

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